Optimal Parameterization Selection for the Brain-Computer Interface

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Abstract: The contribution deals with the optimization of the EEG off-line, single-trial movement classification by means of parameterization tuning. The data we classify represent manifestations of the simple movements performed by the right shoulder (proximal movement) and right index finger (distal movement) of experimental subjects. We implemented several approaches to the EEG parameterization and compared results in order to increase the recognition score. The results are compared with the results from our earlier works and will form a strong basis for the coming experiments with a new EEG database. The target of our experiments is the implementation of the Brain Computer Interface machine recognizing movements performed on one side of the body using the non-invasive EEG scanning.

Key-Words: Brain-Computer Interface, finger movement, shoulder movement, parameterization, classification, hidden Markov models

1 Introduction

The contribution deals with the optimization of the EEG movement classification by means of parameterization tuning.

The data we classify represent manifestations of the simple movements performed by the right shoulder (proximal movement) and right index finger (distal movement) of the experimental subject. The classification of the real movements performed on one side of the body is in general a tougher task than common problem of right/left hand movement classification [7][8], because the classifier cannot rely on the power differences between contra- and ypsi-lateral sensomotoric areas.

We implemented several approaches to the EEG parameterization and compared results in order to increase the recognition score. The results are compared with the results from our earlier works and form a strong basis for the coming experiments with a new EEG database. Our work was aimed to increase the classification score as much as possible and thus to overcome the ubiquitous interpersonal differences in the classification score [11].

The target of our experiments is the implementation of the Brain Computer Interface machine recognizing movements performed on one side of the body using the non-invasive EEG scanning.

2 EEG Database

The data we use for our experiments were originally recorded for EEG analysis presented in [1].

Seven healthy subjects took part in the experiment, all of them gave written consent prior to the recording. Subjects were sitting in a comfortable chair inside a dim shielded room and were instructed to voluntarily perform movements at irregular intervals (12-15 sec). This is an advantage of the presented study – it is quite common that some perceptual clues are presented to the experimental subjects during EEG recording which can positively influence the resulting system and classification score, as well [12]. All the subjects were right-handed.

Two movements were performed: the proximal and distal ones [1]:

Proximal movement: brisk elevation of the right acromion by about 2cm.

Distal movement: brisk flexion of the right index finger at the proximal metacarpophalangeal joint.

Each subject had an opportunity to practice movements prior to the recording.

The data was continuously recorded from 59 scalp positions distributed over both hemispheres, the sample rate was 500Hz. Data were filtered into 0-100Hz band. Surface EMG and EOG were recorded as well. The EEG was recorded at the surface of the scalp.

In the subsequent processing the EEG with any artifacts was removed and the data were filtered with a surface Laplacian operator employing 8 neighboring electrodes [5]. Then the data were divided into 10sec long epochs with the movement onset in the 5^{th} second (time instant 5.00 sec).

The detailed recorded EEG analysis is to be found in [1]. There are three major phenomena accompanying the movement:

μ/β event-related desynchronization (μ/βERD) – the fall of the power in μ (5-13 Hz) and β (13-40 Hz) band accompanying the movement β **event-related synchronization (βERS)** – the power increase which comes approx. one second after the movement in β band.

3 Classifier Design

The used classification system is a universal one, the same that was used in our other EEG BCI works [2],[3],[4],[14],and [16].

The core of the system is built up on the Hidden Markov Toolkit originally developed by Professor Young [15]. A complete framework for EEG processing implemented in Matlab, C++ and shell was built around this tool. The three major parts were added to the whole system:

parameterization system written in Matlab which is used instead of the standard HTK Hcode utility. All the below mentioned parameterizations were implemented; the input to this block is the raw EEG, the output is parameterized one in the HTK format.

randomization procedure and supporting C++ utilities is responsible for the mitigation of the effect of the small training and testing set (we have only approx. 100 realizations per movement, person and electrode). Each classification experiment was run for 30 times with different (and random) division of EEG realizations between the disjunctive training (60% of realizations) and testing (40% of realizations) sets. This helps us to get reliable results independent on the concrete selected training and testing EEG realizations. [4], [2].

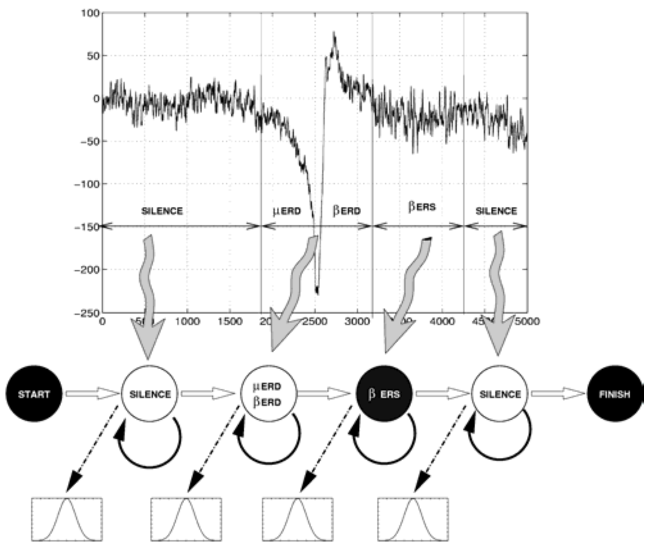

Fig. 1: Model architecture and its correspondence to the real EEG shape. The first and last emitting state model the silence before and after the movement. The second emitting state holds the μ/βERD characteristics and the third one is related to βERS.

classification scores evaluation procedure module collected the 30 results of independent runs and computed means and standard deviations of the classification scores. Only those aggregated numbers were used for comparison of the parameterizations.

4 Classification

Hidden Markov model classifier is the core of our system [3],[16],[17]. The used models have the following parameters:

4 emitting states modelling the four significant phases of movement-related EEG [1],[16] (silence, desynchronization, post-movement synchronization, silence)

left-to-right, no skips architecture which models the sequence of the phases (see Fig. 1).

The whole classification process is based on the conditional likelihood $P(\lambda|R)$ computation, where λ is the selected model (distal or proximal) and R is the parameterized movement realization. See Fig. 2 for the flowchart of the whole classification.

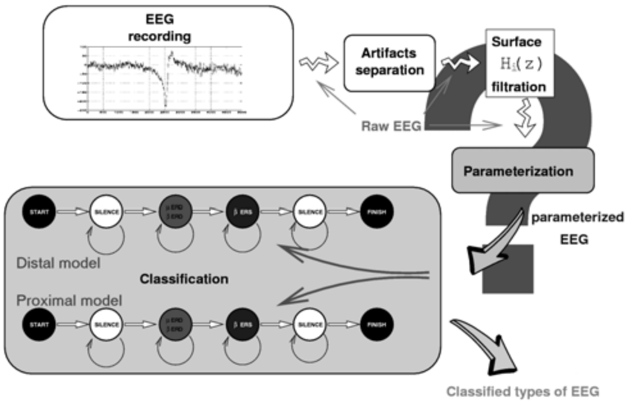

Fig. 2: The recorded EEG is analyzed, the epochs with artifacts are discarded. Then the surface filtration follows to increase the SNR of the signal. The signal is parameterized, the appropriate model is selected and the EEG is classified – information is assigned to the realization on the base of the selected distal or proximal models.

The selected architecture have the following advantages:

ability to model the EEG: we are able to generate synthetic realizations of the EEG for tests of various algorithms.

physiological compatibility: the selected 4-state architecture matches the physiological process, it is even possible to segment the EEG with the help of the Hidden Markov model classifier (on the base of the trained transition matrices) – see [3], [4].

ease of the interpretation – it is quite simple to interpret the contents of the trained model. This is a big advantage compared to e.g. some kinds of neural networks, where the implementation of the trained system is not so straightforward.

utilization of the context information – the system uses the temporary context of the EEG to improve the classification score.

5 Parameterization

Various parameterizations were analyzed and the results were compared with the baseline results published in [3]. We tested the following approaches:

linear prediction coefficients: AR model of the sixth order was used. The order was estimated with the help of appropriate criterions (AIC, FPE, SBC, HQ and PHI were compared – [2],[18]) and is in a compliance with other findings [8]. The parameter vector consisted of 6 LPC coefficients.

linear prediction coefficients + delta: delta coefficients (the first difference) were added to the parameterization vector. The delta coefficients were computed as the first derivations of the LPC time course polynomial approximation [2]. The parameter vector here was composed of 6 LPC + 6 deltas.

reflection coefficients: coefficients of the lattice modeling filter computed with the help of the Levinson recursion. The parameter vector contained 6 reflection coefficients.

FFT parameterization: the magnitudes of the 40 spectral lines (1-41 Hz) were used for parameterization [3]. The parameter vector had 40 coefficients, no windowing was applied.

The reached classification scores for all these parameterization were compared and the appropriate conclusions drawn.

Further, we tried to change some architecture parameters in order to better model the process:

tying of the first and the last emitting HMM states: the 1st and 4th HMM state models the silence before and after the movement. Their tying was seen as a possible way how to further improve the classification score.

combination of the electrodes: the input parameter vector was combined out of three electrodes lying over the sensomotoric cortex to combine all the parameters into one stream.

As the input to the parametrizator we used EEG recorded from electrodes no. 25, 26 and 27 which were positioned over the contralateral sensomotoric cortex – approximate positions C5 (el. 25), C3 (el. 26) and C1 (el. 27) according to 10-20 system [6]. According to our previous research [3] we used 1 second long window with 200msec time resolution for parameters calculation (500 samples window length, 100 samples window step, 400 samples overlap at fs = 500Hz).

6 Results

With the presented settings and for all the persons and parameterizations we executed classification experiments and process and gather the results with help of the developed tools. The classification was computed for electrodes 25 (≈C5), 26 (≈C3) and 27 (≈C1). For each of the persons, the electrode with the highest classification score was chosen ("the best electrode" in the next text).

Summary of the best reached classification results is presented in Table 1. Tables 2, 3 and 4 present the best results of classification with FFT, LPC and LPC+delta parameterizations.

The results shows clear trends:

1. it is obvious that in the future one can consider only two parameterizations (from the described): LPC+delta and FFT.

2. adding delta coefficients to the LPC stream improved the classification for all persons but no. 7 (slight alteration of results) and 3 (proximal score increased, distal decreased).

3. we do not present the reflection coefficients parameterization classification results because they were not good. The parameterization simply did not work as expected.

4. tying of the first and the last state. Obviously, the silence period after the movement exhibits different properties than the silence before the movement.

5. the classification results show large variability across the electrodes used for classification. For majority of the persons is the best electrode classification score rather different from the scores at the remaining electrodes (difference for 10% ÷ 45%).

6. the combination of all electrodes into one stream was not helpful as well. This is the result of the differences in classification scores between electrodes. If one combines all the electrodes into one stream, the resulting interesting EEG components from one electrode will be buried into the "noise" (spontaneous activity, etc.) recorded at the remaining electrodes.

7 Conclusion

Apparently, we were able to further increase the recognition score compared to the values published in [3], [16], and [17].

In addition to classical works – e.g. [8],[19] - we tested LPC+delta and reflective parameterizations. The delta coefficients resulted in the increase of the recognition score. We classified EEG accompanying movement done only on one side of the body, which is a more difficult task than left-right hand movement classification [7],[8] or mental states discrimination [10] commonly used in literature.

The most common best electrode (no. 27) is located approximately over the part of the sensomotoric cortex responsible for fingers and shoulder control. This indicates that the subtle differences in EEG signal accompanying both movements could be used for a real computer control.

Further, it is clear that even the optimal parameterization might be different for different persons. The classification of the EEG signal might be further improved with the optimal individual parameterization selection in addition to common optimal frequency band settings [10].

person no.	ptype	electrode	score prox.	score dist.
1	LPC+Δ	27	86%	89%
2	FFT	25	62%	70%
3	FFT	27	71%	68%
4	FFT	27	71%	99%
5	LPC+Δ	27	72%	72%
6	LPC+Δ	27	89%	90%
7	FFT	26	68%	76%

Table 1: The resulting classification score – the **best** results rounded to the two significant digits. Column *ptype* holds the best parameterization which reaches the score, *electrode* is the electrode which EEG reaches the best results and *proximal/distal scores* are classification scores of both movements.

person no.	electrode	score prox.	score dist.
1	27	53%	81%
2	25	59%	83%
3	25	71%	68%
4	27	71%	99%
5	26	69%	70%
6	25	70%	99%
7	26	68%	76%

Table 2: The classification score reached with the help of the FFT parameterization. The best electrode used for the classification varies across all electrodes.

person no.	electrode	score prox.	score dist.
1	27	67%	83%
2	27	56%	65%
3	26	52%	61%
4	27	61%	64%
5	27	61%	70%
6	27	85%	85%
7	27	73%	66%

Table 3: The classification results reached with pure LPC coefficients without deltas. Mention the electrode stability.

person no.	electrode	score prox.	score dist.
1	27	86%	89%
2	27	66%	67%
3	26	55%	55%
4	27	78%	64%
5	25	72%	72%
6	27	89%	90%
7	27	65%	74%

Table 4: The classification score reached with the help of the LPC+Δ parameterization. The best electrode is nearly always the same.

The next step in our work is to apply the best parameterizations on a new EEG database we recorded recently and results published in [13] to test the limits of this approach. Our work is targeted to the development of a prototype BCI device.

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